

# Implicit Prices of Attributes of Fine German Riesling: Magnitude and Heterogeneity

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The article was published in *British Food Journal*. Suggested citation: Fedoseev, V., Fedoseeva, S. and Herrmann, R. (2023), "Implicit prices of attributes of fine German Riesling: magnitude and heterogeneity", *British Food Journal*, Vol. 125 No. 4, pp. 1245-1262. <https://doi.org/10.1108/BFJ-02-2022-0108>. This is the Author Accepted Manuscript (AAM) as accepted for publication by the journal's Editor on July 12, 2022. The AAM is deposited under the Creative Commons Attribution Non-commercial International Licence 4.0 (CC BY-NC 4.0); any reuse is allowed in accordance with the terms outlined by the licence.

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**Financial Support:** The authors are thankful for the funding by Deutsche Forschungsgemeinschaft (DFG), FE 1830/1-1, received by Svetlana Fedoseeva.

**Conflict of Interest:** None.

**Authorship:** All authors contributed to the manuscript equally. The authors are listed in alphabetical order.

**Ethical Standards Disclosure:** Not applicable since no data on human participants are utilised.

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## Abstract

*Purpose:* The authors analyse how wine attributes affect prices of fine German Riesling wines, provide estimates of the magnitude and heterogeneity of the attributes' implicit prices and draw conclusions on the pricing of fine wine and the research methodology.

*Design/methodology/approach:* Implicit prices of attributes of fine German Rieslings are estimated with fixed-effects regressions and their heterogeneity across quantiles of the conditional price distribution is tested with quantile-regression techniques. The analysis is based on a unique online data set for prices and characteristics of collectible wines.

*Findings:* Quality levels according to the German Prädikat system, additional quality awards for exceptional quality, the wine region, age or vintage as well as ullage and the bottle condition are relevant when explaining the price of cellarable wine. Additionally, the influence of the firm's individual reputation is very strong. Relative price premiums for some major attributes of fine German Riesling change significantly across quantiles of the conditional price distribution. Other attributes are characterized by a rather stable relative (but not absolute) price premium.

*Originality/value:* This is, to the best of our knowledge, the first hedonic price analysis which concentrates exclusively on fine German Riesling wine. By applying both classical and quantile regressions, the authors are able to derive new insights on quality-price linkages in this growing segment of collectible wine and on the research methodology.

*Keywords:* Implicit prices, product attributes, fine wine, quantile regression, German Riesling

## 1. Introduction

The influence of wine attributes on implicit prices and people's willingness to pay for these attributes have been one of the most intensely and carefully explored issues in hedonic price studies (Oczkowski and Doucouliagos, 2015) and in wine marketing and consumer research (Lockshin and Corsi, 2012). An increasing number and share of hedonic wine market studies have concentrated on "fine wine". There is, however, no uniform definition of fine wine in the literature. In their review, Le Fur and Outreville (2019: 196) conclude that the term "is reserved for exceptional wines from the world's best vineyards, the highest quality grapes and the most acclaimed winemakers" which can be sold in well-known auction houses.

Additionally, fine wine can be stored for many years, and its value may increase by ageing (Storchmann, 2012). It is these properties which make it possible to invest in “fine wine” with a potential return that is not possible for “normal wine” (Baldi et al., 2013). Generally, such fine wines, as opposed to normal wines, occupy a very small niche in the wine market. Nevertheless, fine wines belong to one of the best-performing collectibles, topping by far art, jewelry, cars and other luxury assets in terms of year-on-year value growth (Frank, 2017).

The majority of hedonic price studies for fine wine are related to French red wines, mainly from Bordeaux (Le Fur and Outreville, 2019). German Riesling has received much less attention in the growing hedonic price literature on the world's finest wines. This is surprising, as German Rieslings belong to the most expensive collectibles alongside rare red vintages from Bordeaux, Burgundy and Northern Italy. In 2015, six of the 10 most expensive white wines were from Germany (Selva, 2016), and the 2003 Egon Müller’s Scharzhofberg Riesling Trockenbeerenauslese saw the highest price at which a bottle changed hands at one of the recent Mosel auctions (Millar, 2015). Although hedonic studies of German wines, including Riesling, exist, they often focus on the lower-priced and medium-priced segments.

Given this background, it is the objective of this paper to investigate the influence of product characteristics on prices of fine German Riesling wine. As a first step, we estimate implicit prices for individual wine attributes at the conditional mean as is done in most hedonic wine studies. We gain significant insights into the average impacts of important wine characteristics on prices of fine Riesling, and results can be compared with those from existing hedonic studies on fine French red wines or on the “normal” market for German wine.

The standard approach cannot reveal the possible heterogeneity of the effects of product attributes at different points in the conditional price distribution. If responses to product attributes vary across the conditional distribution, estimated (mean) implicit prices provide an incomplete summary of the more complex ways in which product attributes contribute to price formation. As a second step, therefore, we use quantile regressions to capture this heterogeneity. We extend the debate on heterogeneity of implicit prices in three ways. First, by focusing on a single grape variety, single country and single distribution channel, we limit the sources of external heterogeneity that might affect wine price premiums. Second, we argue that the quantile regression framework allows us to address both individual and collective reputation within a single econometric model by providing implicit prices for

individual wine-growing regions, while wines of producers with differentiated price premiums are allocated along the conditional price distribution. Third, we initiate a more thorough debate on relative versus absolute price premiums when computing implicit prices and demonstrate a way to arrive at absolute price premiums from relative effects in a quantile-regression framework.

We use online price data for fine German Rieslings. Given the unique ability to age (Haeger, 2016), cellarable Rieslings include vintages that extend over decades, wine regions, quality levels within the German Prädikat system and bottle conditions, all of which might be potential sources of implicit price heterogeneity. As fine Rieslings experience their renaissance on the market, obtaining accurate measures of price premiums associated with particular wine attributes becomes increasingly important for all the parties involved. As a result, our research design and findings have a few important implications. For producers, these might provide a measure of their returns to investments in producing top late-harvested styles such as Beerenauslese, Trockenbeerenauslese and Eiswein, which are weather-dependent and hence risky. For traders as well as collectors, such estimates may help to evaluate what to expect from the wine price when the wine ages or the bottle condition changes. For research in general, shifting the focus away from conditional means towards conditional distributions may provide an additional impulse to reconsider research design in situations where relationships between variables are too complex to be explained by minimizing the sum of squared residuals.

The remainder of the article is organised as follows. A short review of related literature is given in Section 2. In Section 3, the empirical hedonic price model and the data are introduced. The empirical results are presented and discussed in Section 4. In Section 4.1, fixed-effects regression models are used to estimate and evaluate alternative specifications of the general hedonic model. A major focus is on the choice of age versus vintage effects and the role of individual versus collective reputation. In Section 4.2 we then present a detailed pattern of quantile-specific implicit prices of main attributes of German Riesling and discuss the quantile-regression results. In Section 5 we present our conclusions.

## **2. Previous literature**

A large variety of hedonic studies exists on the influence of wine quality on wine prices (for surveys, see Oczkowski and Doucoulagios, 2015; Le Fur and Outreville, 2019). As a

background for our own empirical model and analysis, we concentrate our brief survey on three segments of the wine literature: (i) studies that identified the importance of major determinants of fine wine prices; (ii) existing work on German wine, in particular Riesling, and the German wine market; and (iii) the small segment of studies dealing with the heterogeneity of price premiums for wine quality attributes.

There is ample evidence that objective quality as measured by wine characteristics shown on wine labels has a powerful effect on wine prices (Combris *et al.*, 1997). Sensoric wine attributes also play a part but their influence seems to be weaker (Cardebat and Figuet, 2004). However, methodological approaches to the measurement of the relative importance of objective versus sensoric characteristics remain an issue (Thrane, 2009; Saïdi and Giraud, 2020). Other contributions are based on the economics of reputation and refer to individual and/or collective reputation. Objective wine characteristics such as the variety, the regional origin or membership in producer groups are indicators of collective reputation, and the names of single wineries indicate individual reputation. Both kinds of reputation play an important role for wine prices (Landon and Smith, 1998; Schamel and Anderson, 2003). When the relative importance of objective wine attributes, sensoric characteristics and reputation variables are compared, there is some evidence that objective and reputation variables are most important (Benfratello *et al.*, 2009). Reputation appears to play a greater role than sensoric traits, whereas the latter are important determinants of jury grades when expert tasters assess the quality of fine wines (Lecocq and Visser, 2006; Cacchiarelli *et al.*, 2016).

Expert reviews affect the demand for wine (Friberg and Grönqvist, 2012), and grading by experts has been shown to influence prices of fine French wines (Ali *et al.*, 2010; Jones and Storchmann, 2001). In a different approach, Ashenfelter (2008) suggested using econometric model to explain Bordeaux wine prices and quality based on the age of the wine and weather variables for the year of vintage rather than relying on more subjective expert opinions and language. In extensions of this modeling type, hedonic pricing approaches were applied in order to investigate the impacts of temperature on wine prices and producers' incentives (Ashenfelter and Storchmann, 2010).

Studies of German wines or the German wine market have typically been conducted for the lower-priced and medium-priced segments of the market that in terms of quantity are most important. Several of these studies (Seidemann, 2000; Szolnoki, 2007) combined the results

of consumer surveys and hedonic price analyses. Wine marketing variables, such as the bottle design or the wine image, have been addressed apart from objective quality indicators. Other authors have investigated how official quality tests of wines in Germany affect wine prices (Schamel, 2003; Schäufele *et al.*, 2016), again more for major consumer segments of the wine market than for the top-quality and top-price levels. A hedonic model of the U.S. consumer market for Riesling includes international competition and considers an aggregate dummy variable for the German origin (Asgari *et al.*, 2016). Some recent studies incorporated the highest quality German wines as well as normal wines, for example Ashenfelter and Storchmann (2010) when analyzing wine prices and winery revenues in the Mosel Valley under the influence of climate change, Frick and Simmons (2013) in their study of the impact of private and collective reputation on producer prices of Riesling wines in the Mosel Valley, and Niklas and Rinke (2020) in their models of wine prices under the influence of weather and quality variables. Our data allows us to concentrate on fine German Riesling wine from various regions and to consider each quality level individually within the German Prädikat system. Thus, the analysis will highlight how each of these wine attributes affects wine prices and demonstrate that price premiums vary greatly across individual product attributes and quantiles of the conditional price distribution.

Methodologically, Costanigro *et al.* (2010) was the first study to use quantile regression to test for heterogeneity and analyze the impact of reputation on wine price segmentation. The authors argue that in the world of different product qualities in which brands act as an insurance against negative experiences, "the reputation premia migrate from collective to specific names as the prices increase" (*ibid.*, p. 1,348). A few studies used quantile regression to assess heterogeneity of implicit prices for wine attributes. They refer to quality cues (Cacciarelli *et al.*, 2016) and distributional channels (Rebelo *et al.*, 2019) as sources of such heterogeneity in (conditional) prices of Italian and Portuguese wines. Most recently, Amédée-Manesme *et al.* (2020) applied quantile regression to test for heterogeneity of implicit prices for the fine wines of Bordeaux. Niklas and Rinke (2020) combined tools of hedonic analysis and machine learning to test whether different price models are needed for different German wines. In our study, we aim to reduce the sources of external heterogeneity (other grape sorts, countries of production or distribution channels) and expand the existing evidence by the application of quantile regression to market prices for fine German Riesling.

### 3. Hedonic price model and data

#### 3.1. Empirical specification

The general idea of a hedonic price function rests on the assumption that goods are valued for their utility-generating attributes that consumers evaluate when making buying decisions (Rosen, 1974), which implies that the competitive market price of product  $i$  ( $Price_i$ ) is the sum of implicit prices paid for particular product traits  $z_n$ :

$$Price_i = Price_i(z_1, z_2, \dots, z_n). \quad (1)$$

The existing wine market literature suggests that wine prices are strongly affected by indicators of objective quality and (collective and private) reputation (see Section 2). In the empirical part we use information on wine characteristics available on the seller's webpage and attribute those to objective quality and reputation. Equation (2) is our general empirical model to quantify Riesling prices as a function of its attributes. We estimate various submodels of equation (2) in the empirical part:

$$\begin{aligned} Price_i = & a + \sum_{l=1}^5 b_l \cdot Prädikat_i + \sum_{m=1}^3 c_m \cdot Ullage_i + \sum_{n=1}^3 d_n \cdot Special_i + \sum_{o=j=1}^{1(3)} e_o \cdot \\ & Age_i^j + (\sum_{p=1}^{94} f_p \cdot Vintage_i) + \sum_{q=1}^3 g_q \cdot Condition_i + \sum_{r=1}^6 h_r \cdot Region_i + (\sum_{s=1}^{151} k_s \cdot \\ & Producer_i) + u_i \end{aligned} \quad (2)$$

The dependent variable  $Price$  is the logarithm of the price of a bottle of wine  $i$  per litre. The first five regressors are vectors of variables characterising the objective quality of a wine. *Prädikat* captures the quality classes of the German *Prädikat* system by dummy variables. Individual variables and price summary statistics across individual categories are presented in the section 3.2. *Ullage* reflects the fill level of the bottle. *Special* is a vector of additional wine attributes and includes three binary variables for awards or the wine style: a dummy for *Goldkapsel*, an additional designation to denote outstanding quality within the *Prädikat* system, as well as an explicit statement on the bottle that the wine is an *Auction* wine or *Dry*. *Age* stands for age-related variables of each bottle. In the linear model, *Age* is a metric variable that describes the age in years (as a difference between 2017 – the youngest vintage in the sample – and the year of the vintage). In line with existing research, we also test for non-linear age effects by augmenting the model with polynomials of *Age*. *Vintage* consists of binary variables that take the value 1 if wine was produced in a particular year and is 0 otherwise.  $b, c, d, e$  and  $f$  are (vectors of) regression coefficients for the marginal impact of objective quality on price. *Condition* reflects the information regarding the label/capsule, i.e.

the condition of the bottle. Other variables of collective and individual reputation include the geographical origin of the wine (*Region*) or the name of its *Producer*.  $g$ ,  $h$  and  $k$  are the vectors of regression coefficients for measuring the marginal impact of *Region* or *Producer* reputation and *Condition* on the wine price.

Apart from *Age*, all these variables are extracted from the retailer's webpage and used as provided. In our sample we only have Riesling for which a Prädikat level is available. When choosing the reference category in the empirical specification, we intended to characterise a base quality of the sample with the base price being the constant when all categorical variables are set to their reference values. For instance, since the majority of wines in our sample are relatively young and in good condition with no outstanding quality awards, our reference category for *Condition* is excellent, for *Ullage* it is full neck and for *Goldkapsel*, *Dry*, or *Auction* it is wine without these features. For the *Region* and *Prädikat* we chose the least expensive groups according to the sample mean prices.

### 3.2. Price data and descriptive statistics

The price quotes are collected from [jahrhundertweine.de](http://jahrhundertweine.de), a German-based online retailer who specialises in trade in rare fine wines from all over the world. The assortment includes over 50,000 wines from four centuries, including the worldwide best choice (shop's own words) of Egon Müller's Rieslings, that rarely make it to traditional wine shops and are mostly sold via auctions. At the time of data collection (November 21, 2018), there were 2,883 German Rieslings with Prädikat for which the price was stated in the retailer's assortment. For each wine, information from its label (region, producer, vintage, quality level) as well as its price per bottle and per litre, the ullage, the state of the capsule and the label, plus whether each particular bottle belongs to the auction wines, has a Goldkapsel or includes "dry" mentioned on the product page is extracted. Table I presents summary statistics across categorical variables.

[Table I]

On average, prices are higher for the highest Prädikat levels (*Beerenauslese*, *Eiswein* and *Trockenbeerenauslese*), for bottles in a damaged or unknown condition and ullage of 3-5 cm to the neck (both of which might well be linked to the age of the respective bottles), for Rieslings from Rheingau, Pfalz and Mosel-Saar-Ruwer regions, and for auction wines with



Goldkapsel. Most wines in our sample are relatively young with a potential to increase their value by ageing: about 15% of the sample are younger than 5 years; 50% are younger than 25 years; 39 wines were produced over a century ago. Riesling prices tend to increase with the age of wine, although this relation is influenced by the quality of individual vintages.

The most expensive wine in the sample is a Steinberger Riesling Trockenbeerenauslese 1893 from Rheingau, Königlich Preussische Domänenkellerei (which today would be one of the Eberbach Abbey sites). The bottle is in a good condition with an ullage of 5 cm. The wine has no Goldkapsel and was not auctioned. In the shop, the 0.75-litre bottle was available at the price of 35,000 Euro.

## 4. Empirical results

### 4.1 Age vs vintage effects and individual vs collective reputation

Since the importance of individual vintages and producers is often discussed in the empirical literature, Table II summarises results from different specifications of Equation (2). Model 1 includes the full set of producer-specific and vintage-specific variables and is able to explain most of the variation in prices (Adj. R-sq. = 0.89). Substituting *Vintage* variables by *Age*, either by a third-degree polynomial or in linear form, results in comparable outcomes (Adj. R-sq. of 0.88 and 0.87 in Models 2 and 3 respectively). In line with Wood and Anderson (2006), the returns to age on wine prices are nonlinear in Model 2. The estimated price premium for *Age* increases up to a certain point (roughly 70 years) and then starts to decline. It becomes negative at about 138 years. The specification that does not model nonlinearity (Model 3) provides us with an estimate of the average annual impact of age on wine prices. Figure 1 plots the individual estimated vintage effects (a) as well as the estimated age coefficient (b) from Models 1 and 2 respectively.

[Table II]

Supplementary material A lists the top-20 highest estimated producer-specific effects from Model 1 in Table II whose price premiums are more than 100% above the price of the reference category. Well-known wine producers are associated with the highest price premiums. Egon Müller tops the list with by far the highest price premium associated with the domain (+1,035%). Figure 2 splits producers into four groups depending on the size of the estimated producer-specific relative price premium and the regional origin. The highest price

premiums in our sample are associated with producers from Mosel-Saar-Ruwer. Mosel producers especially are overrepresented in the group with a price premium above 100% relative to the reference group: 60% of the wines here are from Mosel, while they constitute only roughly 40% of the sample.

[Figure 1]

In Model 4, we substitute regional origin for producer-specific effects. Once individual producer effects are eliminated from the model, the bottle condition becomes relevant for wine prices: all coefficients are statistically significant. Additionally, price premiums for *Goldkapsel*, *Auction* and *Kabinett* increase, while price premiums for *Beerenauslese* and *Eiswein* go down slightly. The signs and statistical significance of other regressors remain largely unaffected. Given that producers with higher and lower reputation coexist within each region, regional price premiums estimated at the conditional mean as in Table II serve as an approximation of more complex links between an individual producer's reputation and the associated prices.

[Figure 2]

Unfortunately, Models 1 to 3 cannot be used as base models for the quantile regressions in the next section since they contain individual effects of vintages and/or producers. Too many additional coefficients have to be estimated and the quantile regressions fail to converge. We rather use Model 4 which appears to be a viable option. Its R-squared is close to 0.7, it includes collective regional reputation, and the *Age* effects may well replace *Vintage* effects as the two variables are correlated. Thus, the chosen method will allow us to quantify potentially heterogeneous price premiums for wines that share collective regional reputation but deviate in individual producer reputation within a single econometric model. Estimating the model using quantile regression allows us to estimate and test for heterogeneity in price premiums across quantiles of the conditional price distribution, characterising the effect of wine attributes on the whole conditional distribution of prices.

#### 4.2. Quantile regression results

In this section we begin with relative price premiums that we obtained from quantile regression estimates and then derive implicit prices (absolute price premiums). The quantile regression is performed using the Stata *sqreg* command that permits simultaneous estimation

at various quantiles and consequently testing the hypothesis of homogeneity of the estimated effects. Full estimation outcomes are available on request. Table III shows relative price effects for the 10th to 90th percentiles in increments of 0.1.

[Table III]

The quantile regression shows that it is crucial to go beyond average effects and to look at the whole (conditional) price distribution in hedonic analysis. There is evidence of heterogeneous as well as homogeneous effects of the regional origin across the quantiles. For Franken and Nahe, the results of quantile regression are fairly stable as their coefficients do not differ significantly between any pair of quantiles. This stable pattern is combined with a clearly higher relative price premium for Nahe than for Franken, which did not show any statistically significant premium relative to the reference group. For the Pfalz region the relative price premium tends to increase as the price level rises. The pattern is similar for the famous Riesling regions Rheingau and Rheinhessen, where substantial heterogeneity across the quantiles exists as well. In all quantiles, the relative price premiums of Rheingau and Rheinhessen Riesling are very high and above those for Pfalz. This pattern indicates the high collective reputation of Rheinhessen and Rheingau Riesling. The most interesting quantile results are those for Mosel-Saar-Ruwer. Table III and equality tests in Supplementary material B reveal a substantial heterogeneity of the quantile estimates and much lower relative price premiums in the lower than in the higher quantiles. Riesling production in the Mosel area is characterized by a dual structure where lower and normal quality wines co-exist with high and highest quality levels given the differential oenological and climatic conditions in that area (Ashenfelter and Storchmann, 2010; Aspøy, 2019). This dual structure is visible even in our sample of collectible Rieslings. The median price of Mosel-Saar-Ruwer is below the sample median, whereas the regional price premium in Q80 and, in particular, in Q90 is higher than in all other Riesling regions considered. The quantile regression results are in line with the extraordinary international reputation of Mosel-Saar-Ruwer for top-quality Riesling wines.

Homogeneity rather than heterogeneity of coefficients for the *Age* variable is a further important result. Despite the significantly lower coefficient in the first quantile, there is a very stable positive influence of age on price between 2.8 and 3.3 % across the quantiles. This result is closely related to the increasing body of literature on “wine as investment” in which

investment in fine wines has been identified as a viable option. Our result points in the same direction. The high price premiums for *Auction* wines and wines with the *Goldkapsel* - often produced in such little quantities that they do not see “normal” markets - further amplify this point especially in the top quantiles of the conditional price distribution. Our data also reveals another major trend in recent decades: the change towards dry Riesling wines in the top categories (Haeger, 2016) which is visible in the high price premium for the variable *Dry* in the quantile Q90. Dry wines – just like Mosel wines – experience a strongly increasing relative price premium as the price level increases.

Most of the variables referring to the bottle condition show little statistically significant heterogeneity in implicit price premiums across quantiles of the conditional price distribution. The good (relative to excellent) label and capsule condition is associated with a price discount of about 10%, but this effect disappears in the high quantiles. Deviations from the full neck in the level of ullage are negatively discounted.

In order to calculate absolute price premiums from the relative price premiums, we first need to map our sample wines to the quantiles of the conditional price distribution. This is done by calculating residuals from the estimated linear model and allocating the sample prices to quantiles of the conditional price distribution based on the deviation between estimated and actual price. Supplementary material C summarises mean prices for wines of different attributes across estimated conditional quantiles. Although those prices continuously increase through the quantiles, they are not the same as the mean prices of the unconditional price distribution (Supplementary material D). To illustrate this point, consider a Trockenbeerenauslese produced by Schloss Vollrads in 1915, in good condition and with an ullage of 2 cm to the neck, which was auctioned and awarded a Goldkapsel. With its price of 6,950 Euro for an 0.7-liter bottle (9,267 Euro per liter), it belongs to the highest quantile of the unconditional price distribution (more than 90% of the sample are cheaper). Yet in the conditional price distribution it is assigned to the 10th quantile at a price that is considerably lower than expected given its attributes. On the other hand, an Auslese from the vineyards of Robert Weil in Rheingau that was bottled as late as in 2015, filled to the neck, in a good condition without any additional special attributes, is offered at a price of 92 Euro per liter. With this price, the wine belongs to the 10th percentile of the unconditional price

distribution, but it is found in the 90th percentile of the conditional price distribution, suggesting that the price is higher than a simple sum of attribute prices.

The very last 10 percent of the conditional price distribution are predominantly Auslese wines from the Mosel region in excellent condition, filled into the neck, without special attributes, on average 28 years old (median age 15). These are mostly wines from the top Riesling estates of the country: over 100 wines here are from Egon Müller who tops the list of the highest producer-specific relative price premiums in our sample.

Absolute price premiums (Supplementary material E) are calculated by multiplying the relative price premium by the mean conditional price of the reference category in the respective quantile. For most product attributes, the absolute follow the pattern of relative price premiums.

As well as the top-quality classes *Eiswein*, *Trockenbeerenauslese* and *Beerenauslese*, *Age* indicates very stable relative price premiums across the quantiles which are huge (albeit different) in magnitude. The result changes when absolute price premiums are computed. A constant relative price premium of the attribute in all quantiles implies a rising absolute price premium as the (conditional) price increases (Figure 3). It is apparent that the Riesling fine wine market appreciates the high reputation and the age of these high wine quality classes.

[Figure 3]

## 5. Discussion and Conclusions

To our knowledge, this study is the first hedonic price analysis that focuses exclusively on fine German Riesling wine. Therefore, the question arises whether our findings confirm results from related studies of fine French wines or of German wines in broader segments of the market and what conclusions can be drawn from the general hedonic models and quantile regression.

The findings reveal some parallels to French wine with regard to general wine characteristics that affect prices. The quality level, regional origin and age play an important role in determining the prices of fine German Riesling, as has been shown for fine French red wine as well (Landon and Smith, 1998; Costanigro et al., 2007; Amédée-Manesme et al., 2020). However, the French and German wine classification systems differ considerably and quality and regional origin have been defined here according to the German Prädikat system. It is

striking in the general hedonic models in Section 4.1, which show average effects of wine attributes on the wine price, that very high price premiums are associated with the top-quality characteristics of the German wine classification system, i.e. Trockenbeerenauslese, Beerenauslese and Eiswein, and also for the famous Riesling regions Rheinhessen, Rheingau and Mosel-Saar-Ruwer. The implicit prices for these attributes range above 200% and at 180% or more respectively (cf. Table III, last column). The magnitude of these effects does not seem to be unique to the market of fine German Riesling. Some other studies show percentage price premiums for the German wine market above 100% as well for the characteristics Trockenbeerenauslese, Eiswein and Beerenauslese (Frick and Simmons, 2013; Niklas and Rinke, 2020; Schamel, 2003) and a recent study even a premium above 900% for the “normal” wine market reveals a percentage price effect of Trockenbeerenauslese like ours for fine wine (Schäufele et al., 2016). It has to be borne in mind, however, that similar percentage price premiums for fine wine imply much higher absolute price premiums for fine Riesling than on the normal wine market.

Additionally, some hypotheses from the economics of fine wine are confirmed for German Riesling. There is a positive impact of age on price; the return to age is about 3.0% annually and is remarkably stable across the quantiles. Moreover, top-quality labels and good preservation of the bottle of older wines can be expected to raise wine prices. These presumptions are confirmed for the German market by high price premiums for the labels *Goldkapsel* and *Auctions* and by the importance of the ullage respectively. Overall, the individual reputation of winemakers plays a crucial role for the magnitude and heterogeneity of the prices of fine German Riesling and is more important than regional reputation.

It is a major result from quantile regression that the magnitude of implicit prices for individual attributes is highly heterogeneous and might deviate substantially from the OLS estimate of a conditional mean across quantiles of the conditional price distribution. This underlines the importance of expanding the analytical toolkit when analyzing hedonic prices and explicitly testing possible heterogeneity in the impacts of product attributes on prices at different quantiles of the conditional price distribution. Results from quantile regression can be used by producers, traders and collectors alike to make more informed decisions. We also highlight the difference in the relative versus absolute magnitude of premiums across quantiles and propose a way to derive implicit prices from relative price premiums in the quantile-

regression framework. The distinction between relative and absolute price premiums of the attributes has been largely ignored in the hedonic literature and deserves more attention.

Finally, a few notes of caution are needed here. The strength of our study, i.e. to focus on a single grape, country and retailing channel, is simultaneously its limitation. We do not attempt or pretend to be able to explain prices across the entirety of fine cellarable wines. No existing study captures the whole complex picture of quality-price linkages on highly differentiated wine markets. Our results, however, demonstrate that the heterogeneity in implicit prices exists not only across distribution channels and various wine styles, as has been shown earlier, but also within a much more defined and “homogeneous” group. Not only can traditionally considered wine traits like style or age affect implicit prices but also the position in the conditional price distribution, across which the implicit price for a particular product attribute may vary considerably.

It has to be borne in mind, too, that we have elaborated how the observed supply prices of one major online retailer are affected by quality attributes of fine German Riesling. We cannot be sure that the same pattern of pricing would be observed at another point of time, for other retailers or on auction markets for fine wine. Fine wine is traded on a thin market, and interesting subsequent questions remain for future research.

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Figure 1. Estimated vintage-specific effects from Model 1(a) and estimated age coefficient from Model 2(b)

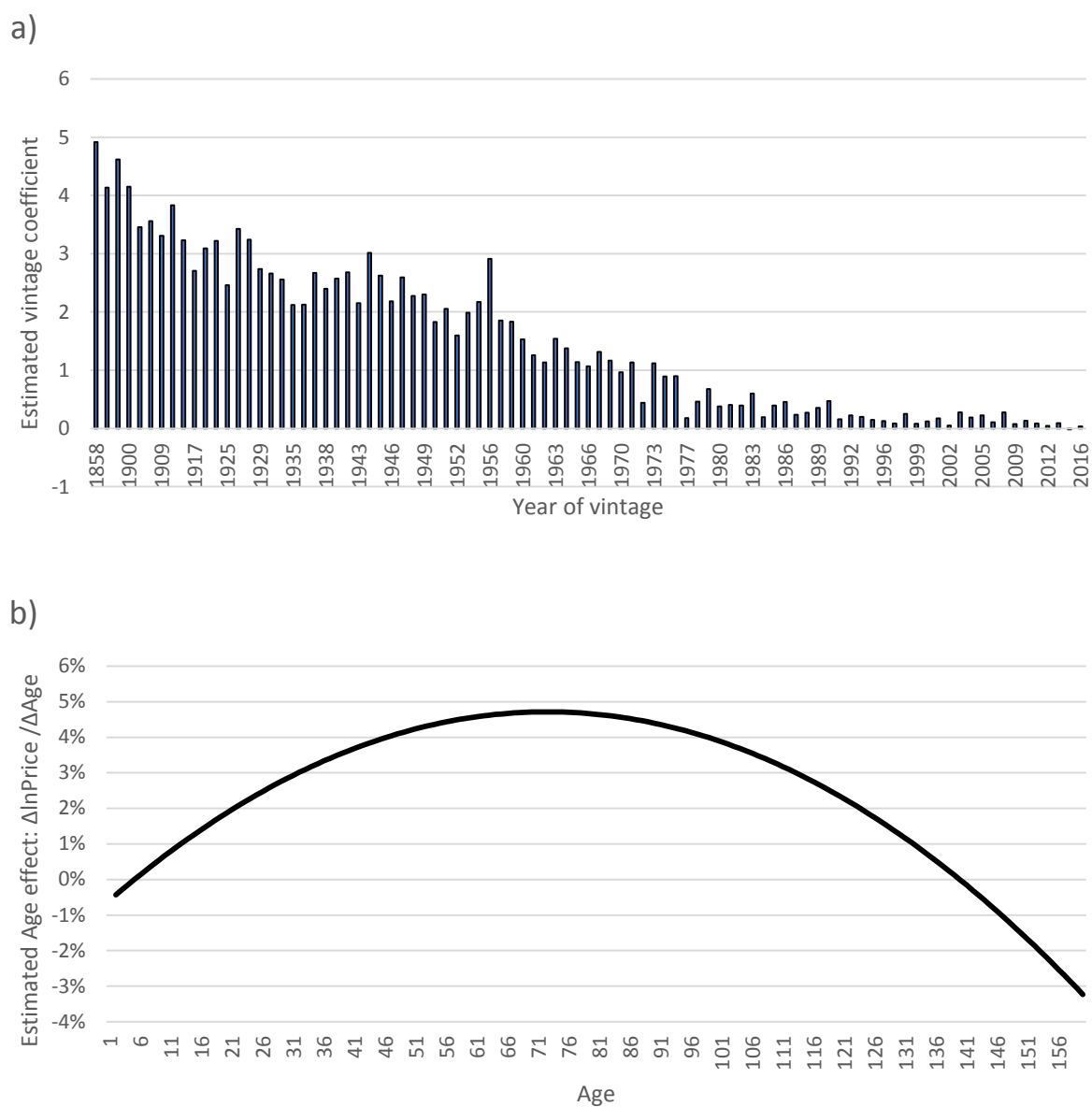
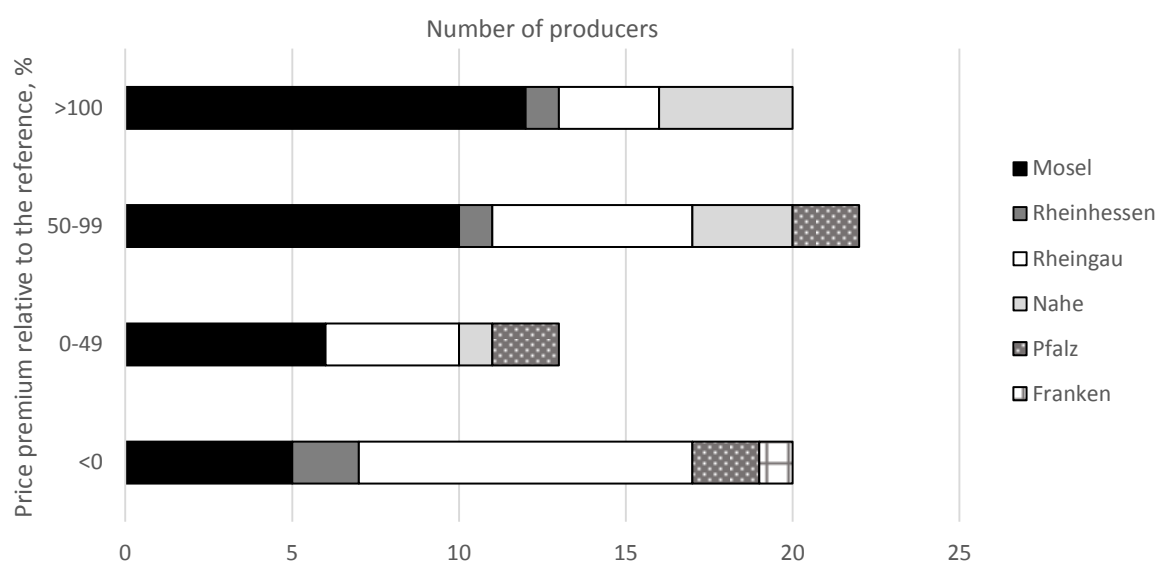
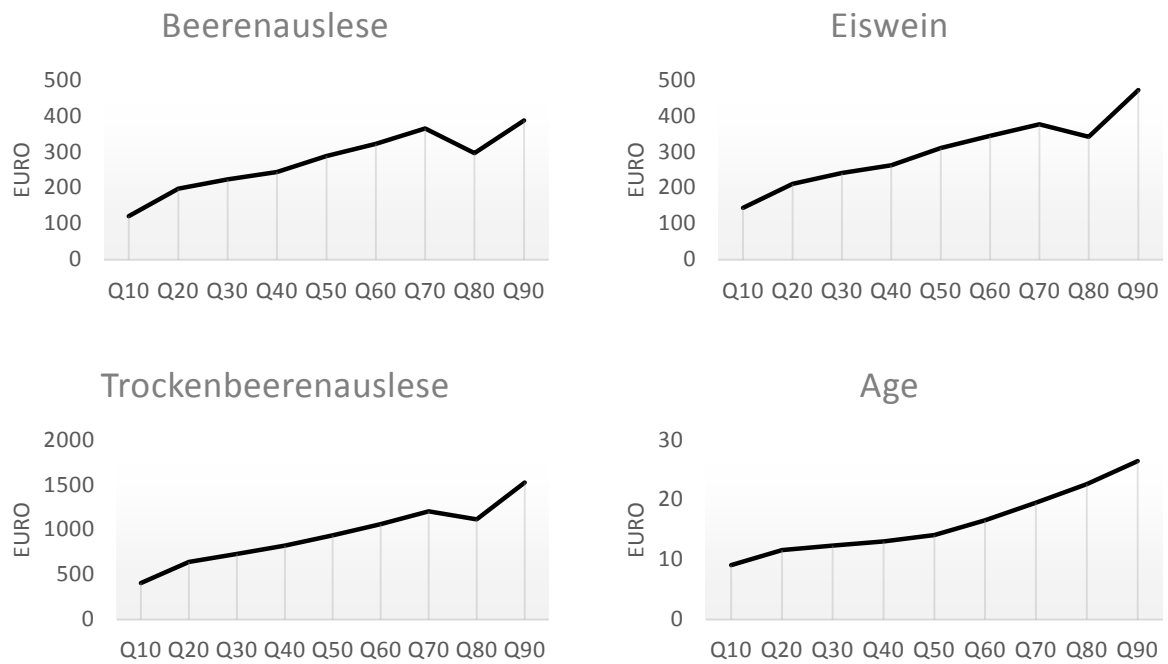


Figure 2. Distribution of regional producers across the estimated producer-specific relative price premiums



Note: The figure does not include producers whose estimated price premium is not statistically different from the reference category at a 5% level.

Figure 3. Absolute price premiums for the top-quality levels and age



Notes: Absolute price premiums (implicit prices) are derived from relative price premiums and mean conditional quantile prices of reference categories.

Table I. Price summary statistics across categories (price per litre in Euro)

		Mean	Median	Min	Max	SD	Obs.	% Obs.
<i>Prädikat</i>	<i>Spätlese*</i>	239	127	13	1300	264	125	4.3
	<i>Auslese</i>	442	167	16	10600	910	947	32.8
	<i>Kabinett</i>	414	260	12	1667	368	59	2.0
	<i>Beerenauslese</i>	797	393	92	11867	1230	551	19.1
	<i>Eiswein</i>	757	333	70	26000	1701	440	15.3
	<i>Trockenbeerenauslese</i>	2518	1000	118	46667	4277	761	26.4
<i>Ullage</i>	<i>Into neck*</i>	925	371	12	26000	2090	2254	78.2
	<i>&lt;3 cm</i>	1439	527	26	39333	2972	398	13.8
	<i>3-5 cm</i>	2198	633	39	46667	4790	229	7.9
	<i>&gt;5 cm</i>	377	377	233	520	203	2	0.1
<i>Special</i>	<i>Goldkapsel: Yes</i>	1207	465	26	26000	2770	996	34.5
	<i>Goldkapsel: No*</i>	1038	387	12	46667	2449	1887	65.5
	<i>Dry: Yes</i>	373	130	17	1853	407	39	9.8
	<i>Dry: No*</i>	1106	393	12	46667	2581	2844	90.2
	<i>Auction: Yes</i>	1519	593	26	25200	2829	393	13.6
	<i>Auction: No*</i>	1030	387	12	46667	2516	2490	86.4
<i>Condition</i>	<i>Excellent*</i>	1044	387	12	39333	2460	1635	56.7
	<i>Good</i>	1153	433	13	46667	2712	1186	41.2
	<i>Damaged</i>	1295	400	52	10600	2204	54	1.9
	<i>N/A</i>	2267	577	84	9933	3429	8	0.2
<i>Region</i>	<i>Franken</i>	297	299	200	387	84	6	0.2
	<i>Mosel-Saar-Ruwer</i>	1207	333	12	39333	2865	1207	41.9
	<i>Nahe</i>	751	333	29	12667	1309	362	12.5
	<i>Pfalz</i>	1140	393	16	16667	1969	138	4.8
	<i>Rheingau</i>	1296	493	17	46667	2826	962	33.4
	<i>Rheinhessen</i>	789	530	25	4333	828	200	6.9
	<i>Other*</i>	176	112	60	371	123	8	0.3
Total		1097	393	12	46667	2566	2883	100.0

Notes: \* indicates the reference category.

Table II. Determinants of wine price

	ln(Price)	ln(Price)	ln(Price)	ln(Price)
	(1)	(2)	(3)	(4)
<i>Auslese</i>	0.54*** (0.05)	0.51*** (0.05)	0.49*** (0.05)	0.45*** (0.07)
<i>Kabinett</i>	0.43*** (0.13)	0.39*** (0.13)	0.48*** (0.13)	0.74*** (0.17)
<i>Beerenauslese</i>	1.52*** (0.05)	1.50*** (0.05)	1.42*** (0.05)	1.30*** (0.07)
<i>Eiswein</i>	1.80*** (0.05)	1.69*** (0.05)	1.57*** (0.05)	1.38*** (0.07)
<i>Trockenbeerenauslese</i>	2.54*** (0.05)	2.52*** (0.05)	2.50*** (0.05)	2.32*** (0.07)
<i>Ullage &lt;3 cm</i>	-0.01 (0.04)	-0.02 (0.04)	0.00 (0.04)	-0.14*** (0.04)
<i>Ullage 3-5 cm</i>	0.02 (0.04)	0.05 (0.04)	0.10** (0.04)	-0.04*** (0.05)
<i>Ullage &gt;5 cm</i>	-1.12 (0.09)	-1.07*** (0.12)	-0.83*** (0.29)	-1.43*** (0.22)
<i>Condition: Good</i>	-0.03 (0.03)	-0.02 (0.03)	-0.03 (0.03)	-0.13*** (0.03)
<i>Condition: Damaged</i>	-0.09 (0.08)	-0.06 (0.08)	-0.01 (0.03)	-0.27** (0.10)
<i>Condition: N/A</i>	-0.03 (0.11)	-0.15 (0.11)	-0.09 (0.06)	-0.34*** (0.13)
<i>Goldkapsel</i>	0.36*** (0.03)	0.36*** (0.03)	0.37*** (0.03)	0.57*** (0.04)
<i>Dry</i>	0.76*** (0.16)	0.75*** (0.17)	0.73*** (0.17)	0.73*** (0.19)
<i>Auction</i>	0.68*** (0.03)	0.64*** (0.03)	0.63*** (0.04)	0.77*** (0.05)

<i>Age</i>	-0.005*	0.034***	0.032***	
	(0.003)	(0.001)	(0.001)	
<i>Age</i> <sup>2</sup>	0.001***			
	(0.000)			
<i>Age</i> <sup>3</sup>	-0.000***			
	(0.000)			
<i>Franken</i>			0.46**	
			(0.20)	
<i>Mosel-Saar-Ruwer</i>			1.15***	
			(0.10)	
<i>Nahe</i>			1.02***	
			(0.10)	
<i>Pfalz</i>			0.88***	
			(0.10)	
<i>Rheingau</i>			1.03***	
			(0.10)	
<i>Rheinhessen</i>			1.19***	
			(0.11)	
<i>Constant</i>	3.18***	3.13***	2.62***	2.53***
	(0.15)	(0.15)	(0.15)	(0.11)
<i>Producer FE</i>	Yes	Yes	Yes	No
<i>Vintage FE</i>	Yes	No	No	No
<i>Adjusted R-sq.</i>	0.89	0.88	0.87	0.68

Source: Own calculation. Notes: \*\*\*p<0.01, \*\*p<0.05, p<0.1. Heteroscedasticity-consistent standard errors are given in parentheses. % price effects for categorical variables can be calculated using adjustments by Halvorsen and Palmquist (1980) as  $(e^{\beta} - 1) * 100$ , where  $\beta$  is the estimated coefficient. Monetary price effects can be calculated relative to the mean price of the base category (Table I).



Table III. Quantile regression results: Price effects in %

		Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90	Model 4 (%)
<i>Prädikat</i>	<i>Auslese</i>	51.76	55.19	53.73	54.43	63.90	56.70	56.67	34.72	31.57	57.55
	<i>Kabinett</i>	-44.93	-15.70	36.85	82.83	347.72	281.82	299.57	219.12	185.93	109.46
	<i>BA</i>	232.94	260.42	266.65	268.21	297.23	288.14	294.89	221.74	219.18	268.81
	<i>Eiswein</i>	276.63	277.55	287.18	288.50	320.94	308.12	304.13	255.23	266.91	296.23
	<i>TBA</i>	780.59	844.11	868.32	905.80	965.72	947.15	970.85	833.71	862.55	916.85
<i>Ullage</i>	<i>&lt;3 cm</i>	1.58	-8.37	-12.27	-9.64	-11.30	-16.38	-19.43	-24.97	-29.19	-13.21
	<i>3-5 cm</i>	-6.94	-1.72	-3.83	-5.39	-6.40	-3.47	-9.67	-14.68	-14.85	-3.56
	<i>&gt;5 cm</i>	-56.13	-67.10	-73.73	-77.25	-80.33	-72.10	-74.10	-77.29	-81.04	-76.24
<i>Special</i>	<i>Goldkapsel</i>	65.89	68.70	68.56	64.33	62.54	60.72	70.71	92.56	97.26	76.44
	<i>Dry</i>	-9.09	15.18	24.60	98.32	85.55	141.25	167.31	173.89	206.29	107.03
	<i>Auction</i>	57.24	66.75	81.24	101.62	134.98	147.42	166.05	158.69	189.37	116.48
<i>Age</i>	<i>Age</i>	2.81	3.08	3.15	3.16	3.18	3.25	3.25	3.27	3.32	3.16
<i>Condition</i>	<i>Good</i>	-11.35	-11.80	-9.38	-12.61	-12.77	-9.11	-6.72	-4.82	-2.41	-12.23
	<i>Damaged</i>	-14.63	-27.20	-18.69	-26.77	-27.58	-23.80	-20.20	-25.32	-14.75	-23.63
	<i>N/A</i>	-15.94	-8.89	-15.58	-28.32	-31.32	-37.54	-45.04	-21.09	-36.61	-28.85
<i>Region</i>	<i>Franken</i>	50.78	51.09	17.71	31.17	60.54	56.68	110.07	115.79	62.31	58.18
	<i>Mosel-Saar-Ruwer</i>	104.28	148.06	139.35	159.25	171.48	215.07	225.73	373.65	425.36	215.26
	<i>Nahe</i>	146.28	188.11	159.50	161.26	162.38	195.17	184.06	239.65	202.55	178.65
	<i>Pfalz</i>	70.59	102.51	136.81	156.64	152.83	175.64	165.64	225.75	191.99	140.35
	<i>Rheingau</i>	108.06	154.70	140.33	165.42	173.79	214.49	221.24	308.67	274.02	179.59
	<i>Rheinhessen</i>	85.09	136.69	146.03	208.55	236.90	304.23	288.05	362.57	313.30	227.83

Notes: The last column presents relative price premiums from Model 4 in which coefficients are estimated at the conditional mean. The price premiums in grey refer to estimates that are statistically significant at <5% in the estimation equation. Price effects in % are calculated as explained in Table II.

Supplementary material A. Producer-specific price premiums, Top-20

Producer	Coeff.	P-value	Price premium (%)	Region
Egon Müller	2.43	0.00	1035	Mosel
Weingut Keller	1.29	0.00	264	Rheinhessen
J. J. Prüm	1.27	0.00	255	Mosel
Robert Weil	1.15	0.00	217	Rheingau
Gut Hermannsberg	1.09	0.00	199	Nahe
Staatsweinbaudomäne Trier	0.94	0.00	155	Nahe
C. von Schubertsche Schlosskellerei	0.91	0.00	147	Mosel
Fritz Haag	0.89	0.00	144	Mosel
Schloss Johannisberg	0.86	0.00	137	Rheingau
Forstmeister Geltz-Zilliken	0.84	0.00	131	Mosel
Jos. Christoffel Jr.	0.82	0.00	128	Mosel
Hermann Dönnhoff	0.79	0.00	120	Nahe
Christoffel-Prüm	0.78	0.00	119	Mosel
Dr. Loosen	0.78	0.00	118	Mosel
Markus Molitor	0.77	0.00	116	Mosel
Emrich-Schönleber	0.75	0.00	111	Nahe
Heymann	0.74	0.00	110	Mosel
Clemens Busch	0.72	0.00	106	Mosel
Peter Jakob Kühn	0.69	0.00	100	Rheingau
Von Othegraven	0.69	0.00	100	Mosel

Note: The price premiums are computed from Model 1 in Table II.

Supplementary material B. Test results of the equality of estimates between quantiles

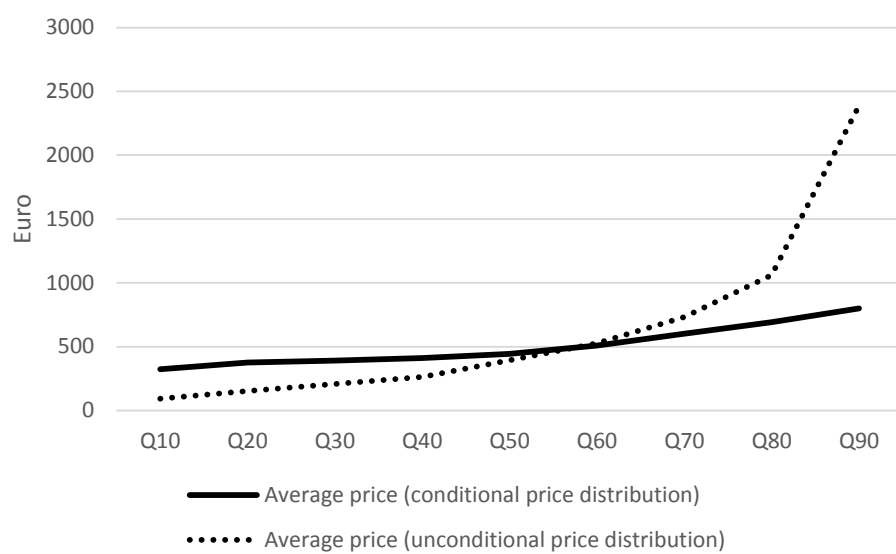
	$H_0: Q_{10}=Q_{20}=Q_{30}=Q_{40}=Q_{50}=Q_{60}=Q_{70}=Q_{80}=Q_{90}$	P-value
<i>Prädikat</i>	<i>Auslese</i>	0.49
	<i>Kabinett</i>	0.00
	<i>BA</i>	0.23
	<i>Eiswein</i>	0.65
	<i>TBA</i>	0.66
<i>Ullage</i>	<i>&lt;3 cm</i>	0.00
	<i>3-5 cm</i>	0.83
	<i>&gt;5 cm</i>	0.00
<i>Special</i>	<i>Goldkapsel</i>	0.09
	<i>Dry</i>	0.01
	<i>Auction</i>	0.00
<i>Age</i>	<i>Age</i>	0.34
<i>Condition</i>	<i>Good</i>	0.50
	<i>Damaged</i>	0.78
	<i>N/A</i>	0.65
<i>Region</i>	<i>Franken</i>	0.87
	<i>Mosel-Saar</i>	0.01
	<i>Nahe</i>	0.83
	<i>Pfalz</i>	0.31
	<i>Rheingau</i>	0.15
	<i>Rheinhessen</i>	0.06

## Supplementary material C. Mean quantile prices of a conditional price distribution

		Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
<i>Prädikat</i>	<i>Kabinett</i>	48	73	170	197	276	326	346	346	330
	<i>Spätlese</i>	52	76	86	91	97	112	124	133	177
	<i>Auslese</i>	98	113	118	129	162	172	204	238	270
	<i>BA</i>	249	273	314	326	360	404	442	518	601
	<i>Eiswein</i>	230	237	268	293	308	321	358	394	447
	<i>TBA</i>	687	920	956	1007	1050	1243	1469	1678	1908
<i>Ullage</i>	<i>Into neck</i>	280	322	344	352	375	421	486	549	630
	<i>&lt;3 cm</i>	676	712	644	725	768	882	994	1057	1251
	<i>3-5 cm</i>	349	456	495	561	665	777	1031	1419	1620
	<i>&gt;5 cm</i>				233	233	233	377	377	377
<i>Goldkapsel</i>	<i>Yes</i>	346	360	348	351	376	555	471	522	632
	<i>No</i>	307	386	420	451	488	433	671	778	884
<i>Dry</i>	<i>Yes</i>	50	101	107	107	109	110	114	114	114
	<i>No</i>	333	383	397	418	450	515	607	698	806
<i>Auction</i>	<i>Yes</i>	457	698	789	778	803	817	860	913	1048
	<i>No</i>	280	300	312	349	389	463	563	659	764
<i>Condition</i>	<i>Excellent</i>	284	399	391	404	427	503	599	643	717
	<i>Good</i>	380	327	381	403	459	512	595	754	898
	<i>Damaged</i>	188	676	640	682	614	585	724	733	826
	<i>N/A</i>			167	2190	950	950	950	950	2267
<i>Region</i>	<i>Franken</i>			232	266	266	296	296	279	279
	<i>Pfalz</i>	480	387	378	388	405	606	570	847	1071
	<i>Mosel-Saar-Ruwer</i>	230	226	250	279	299	348	383	427	538
	<i>Nahe</i>	218	528	421	455	526	581	611	650	728
	<i>Rheingau</i>	391	545	567	554	583	660	874	1003	1104
	<i>Rheinhessen</i>	537	517	575	697	763	776	856	778	818
	<i>Not specified</i>			119	109	160	149	148	176	176
Total		323	376	392	412	444	510	601	691	799

Notes: The wines from the categories Ullage >5cm, Region Franken or not specified, Condition N/A only appear at Q30/40 of the conditional price distribution. Hence no implicit prices for regions were calculated in the lower percentiles.

# Supplementary material D. Average quantile prices of the (un)conditional price distribution



## Supplementary material E. Quantile regression results: Price effects in Euro

	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
<i>Auslese</i>	27	42	45	50	62	64	70	47	56
<i>Kabinett</i>	-23	-12	31	75	337	316	371	294	329
<i>Beerenauslese</i>	121	198	224	244	288	323	366	297	388
<i>Eiswein</i>	144	211	241	263	311	345	377	342	472
<i>Trockenbeerenauslese</i>	406	642	729	824	937	1061	1204	1117	1527
<i>Ullage: &lt;3 cm</i>	4	-27	-42	-34	-42	-69	-94	-137	-184
<i>Ullage: 3-5 cm</i>	-19	-6	-13	-19	-24	-15	-47	-81	-94
<i>Ullage: &gt;5 cm</i>	-157	-216	-254	-272	-301	-304	-360	-424	-511
<i>Goldkapsel</i>	202	265	288	290	306	337	474	720	860
<i>Dry</i>	-30	58	98	411	385	727	1016	1214	1663
<i>Auction</i>	160	200	253	355	525	683	935	1046	1447
<i>Age</i>	9	12	12	13	14	17	20	23	26
<i>Condition: Good</i>	-32	-47	-37	-51	-55	-46	-40	-31	-17
<i>Condition: Damaged</i>	-42	-109	-73	-108	-118	-120	-121	-163	-106
<i>Condition: N/A</i>	-45	-35	-61	-114	-134	-189	-270	-136	-263
<i>Franken</i>			21	34	97	84	163	204	110
<i>Mosel-Saar-Ruwer</i>			166	174	274	320	334	658	749
<i>Nahe</i>			190	176	260	291	272	422	356
<i>Pfalz</i>			163	171	245	262	245	397	338
<i>Rheingau</i>			167	180	278	320	327	543	482
<i>Rheinhessen</i>			174	227	379	453	426	638	551

Notes: The price premiums in grey refer to estimates that are statistically significant at <5% in the quantile regression estimation. Absolute price premiums are derived from relative price premiums (Table III) and mean conditional quantile prices of reference categories (Supplementary material C). The implicit price for age is calculated at the quantile mean price. The wines from the reference category for Region only appear at Q30 of the conditional price distribution. Hence no implicit prices for regions were calculated in Q10-Q20.